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DISSERTATION

AUTOMATION AND LABOR DISPLACEMENT

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*To my family and friends
that supported me during
the hardest times and to
my supervisor for the attentive
guidance. It would not have been
possible without you.*

ERRATUM

1.

GLOSSARY

ATM Automatic Teller Machine. 3, 18

ICT Information and Communications Technology. 3, 5, 7, 11, 12, 16, 18, 24–27, 31–34

IFR International Federation of Robotics. 3

ISCED International Standard Classification of Education. 3, 27

ISCO International Standard Classification of Occupations. 3, 24, 31

OB Oaxaca-Blinder. 3

OECD Organisation for Economic Co-operation and Development. 3, 11, 15, 18, 24, 34

PCA Principal Component Analysis. 3, 25, 38

PIAAC Programme for the International Assessment of Adult Competencies. 3, 11, 24, 34

RTI Routine Task Intensity. 3, 24–28, 31, 32, 34, 42–44

SVD Singular Value Decomposition. 3, 38

US United States. 3, 15, 18, 39

ABSTRACT, KEYWORDS, AND JEL CODES

This dissertation addresses the way technological progress affects the structure of labor market. A theoretical framework based on the routine-biased technical change hypothesis was constructed. The empirical analysis evaluates how the routine task content of occupations is impacted by the adoption of technology at work using a linear model with a fixed-effects estimator. Additionally, the effects of technological adoption at work on the polarization of income were estimated using an Oaxaca-Blinder decomposition. Estimation results indicate that economies with a higher use of technology have fewer routine intensive labor and that income differences between routine (linked to middle-skilled labor) and non-routine labor are higher when the use of technology at the workplace is higher as well.

KEYWORDS: Information and Communication Technologies; Polarization; Routine-biased Technical Change; Technological progress; Routine Task Intensity.

JEL CODES: C38; J21; J24; J31; O14; O33.

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AUTOMATION AND LABOR DISPLACEMENT

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THIS DISSERTATION addresses how technological progress affects the structure of labor market. A theoretical framework based on the routine-biased technical change hypothesis was constructed. The empirical analysis evaluates how the routine task content of occupations is impacted by the adoption of technology at work using a linear model with a fixed-effects estimator. Additionally, the effects of technological adoption at work on the polarization of income were estimated using an Oaxaca-Blinder decomposition. Estimation results indicate that economies with a higher use of technology have fewer routine intensive labor and that income differences between routine (linked to middle-skilled labor) and non-routine labor are higher when the use of technology at the workplace is higher as well.

1 INTRODUCTION

During the beginning of the 1980s, academic researchers started noticing a sharp increase in wage inequality in the United States. An attempt towards explaining such phenomenon led to the development of the skill-biased technological change theory(Katz et al. (1999)). However, this framework was not very successful in explaining two characteristics of this trend.

The first is the non-monotonic nature of employment growth when looking at the skill levels. Skill-biased technical change predicts the growth of employment to be monotonic at the skill level, with low-skill occupations experiencing smaller employment growth with time, contrary to the high-skill occupations. Despite the second part of this implication being correct, as high skill occupations did experience higher employment growth compared to other skill levels, low-skill occupations were also expanding. On the other hand, middle-skill occupations were declining. Therefore, the depiction of the employment growth by skill level in the United States during the 1980s was U-shaped and not monotonically increasing with skill level.

The second characteristic of such a trend concerns the wage changes by skill level referring to the same period. This dissertation is more focused on this characteristic due to the nature of the data that is being used. Similar to the employment growth, wages changed in a non-monotonic way, featuring the same U-shaped curve when displaying the percentual change in wages against the occupational skill level. The skill-biased technological change framework also models correctly the evolution of wages for high-skill occupations. Nevertheless, the low-skill occupation wages grow in a similar fashion as the latter. However, what was seen regarding the employment growth of mid-skill occupations is also applied to the way wages have been evolving, thus contradicting what was predicted from the skill-biased technical change framework. The name attributed to such phenomena is job polarization.

Job polarization can be both the result of supply or demand-driven events. On one hand, the technical progress in the past recent decades has been pushing labor further away from routine tasks. As a result, the labor market demand has been shifting towards jobs that are intensive in non-routine tasks. Given that jobs in both the middle-skill level and middle wage level are considered to be the ones more intensive in routine tasks, the workers within this group are being pushed towards low-skill and lower paid jobs, leading to the so-called job polarization.

On the other hand, the growing literacy of the labor market in the past years can be deemed as a supply-driven event that stimulates the polarization of jobs. An excess supply of middle-skill workers resulting from the higher accessibility to education may result in a saturation of the labor market and hence push the wage levels of these workers downwards.

This dissertation focuses on the effect that technological adoption in the workplace can have on the labor markets. More specifically, two implications from Autor (2013) were tested. According to Autor (2013), a negative shock in the price of computer capital will affect the employment structure of an economy in the following manner:

1. A greater adoption of ICT, which consequently causes a shift of labor from routine tasks by replacing the latter with machinery.
2. Larger wage increases for high-skill Abstract and low-skill Manual labor relative to routine labor.

In order to test both of these hypotheses, two indexes will be constructed. One will be the ICT, which will represent how intense in routine tasks each individual worker's job is. The other index will be the ICT index. This index will measure the intensity of use of the latter technologies at the workplace. It will function as a proxy for technology adoption at work.

After retrieving these indexes, two different empirical analyses will be performed. Firstly, a pooled linear model with a fixed-effects estimator will estimate the effect that technological adoption can have on Routine Task Intensity at work. Secondly, a linear decomposition is applied to assess whether an increase in technological adoption at work will cause larger wage increases in non-routine jobs as opposed to routine jobs.

Since our data is obtained from a survey, the Organisation for Economic Co-operation and Development (OECD)'s Programme for the International Assessment of Adult Competencies (PIAAC), it is not possible to assess the time dynamics of data. One can only study comparative statics.

The empirical analyses showed that higher technological adoption at work is associated with less routine intense labor and that economies with higher technological adoption at work also experienced more pronounced earnings disparity between routine and non-routine groups of workers.

This dissertation is structured as follows: The first section introduces some of the key concepts being discussed throughout the article through a literature review. The second section presents a theoretical framework using an assignment model. The following section demonstrates how the data was retrieved as well as the methodology being used to construct the two indexes .Section 4 displays the empirical analyses and estimation results. The last section provides some concluding remarks as well as suggested topics for further research.

2 LITERATURE REVIEW

2.1 Job polarization

Job Polarization can be defined as the phenomenon in which the employment of high and low wage occupations increases at the cost of middle waged employment. Depending on the workers' education levels, mid-skill workers are pushed either up or down into new occupations. Despite being a fairly recent phenomenon, it puzzles researchers when the question of what causes it is posed.

Several reasons behind this recent phenomenon come to mind when trying to explain the polarization of the labor market. The first and most widely recognized is technical change. The recent developments in technology allow for employers to save more by acquiring machines that perform routine tasks instead of hiring workers. As mentioned above, this has had a pervasive effect on the middle-skill employment.

However, this labor saving effect can reduce the price of output and increase aggregate demand, thus leading to higher labor demand in other sectors. Additionally, assuming that jobs are composed of a wide spectrum of tasks, freeing up workers from routine tasks may increase their productivity. Whether technical progress affects positively or negatively the labor market conditions remains a heated topic of discussion.

Although the recent surge of new capital goods displaces middle-skill labor, recent technical change does not limit itself to displacing jobs. It also complements high-skill labor, making the relative demand for educated jobs much higher. The effect it has on low-skill jobs is mainly neutral since most of these occupations contain either intensive non-routine manual tasks or jobs requiring social interaction.

Another alternative is that offshoring (which can be partly driven by technology) may be driving the demand for middle-skill work downwards (mainly in the manufacturing sector). In a globalized economy, low wage countries' workers can effectively compete with advanced economies' workers and replace their jobs by requiring a substantially smaller wage for essentially the same amount of work. Advancements in ICT technologies and the lowering of international trade costs make interactions among workers in developing economies and firms in advanced economies much easier, thus enabling the former to replace the jobs of workers in advanced economies.

Since these two phenomena are relatively contemporary, distinguishing whether offshoring or technical progress is the main driver causing the labor market polarization appears to be a cumbersome task. It may be even the case that both may share a causality effect (Bloom et al. (2016)).

2.2 Historical analysis of the employment structure

Since the 1990s, the distribution of occupations in advanced economies has been revealing a trend towards the hollowing out of middle-skill jobs. The term 'hollowing out' means that the share of these middle-skill jobs is declining relative to both high-skill and low-skill jobs. This recent phenomenon resembles the deskilling of the manufacturing sector in the nineteenth century, where middle-skill artisans saw their jobs being replaced by machines that could deliver a larger amount of production, despite the lower quality in each product. During this period, US labor shifted significantly out of the agriculture sector, turning this labor into the manufacturing sector and replacing skilled artisans in this sector. This replacement, with low-skill jobs increasing at the expense of middle-skill jobs in the manufacturing sector, may have been the first experience of job polarization ever witnessed. However, just because the manufacturing sector in the nineteenth century displayed this behavior in the labor market, it doesn't mean that the aggregate economy behaved the same way. In fact, from the mid-nineteenth century until the early twentieth century the pattern of labor market behavior followed the skill-biased technical change route, with low-skill labor decreasing, the mid-skilled labor remaining steady, and an increase in high-skill jobs, as well as an increasing college premium. Monotonic skill upgrading is also observable in most of the twentieth century, only fading away as job polarization intensified, which was already in the late twentieth century. Katz and Margo (2014) find a rise in the premium for white-collar workers for most of the nineteenth century. From 1920 to 2010, the share of high-skill employment more than tripled from 12% of employment as of 1920 to 39% by 2010. As for the middle-skill group, it remained steady throughout most of the twentieth century (from 1920 to 1980). However, underneath the steadiness, there were already some changes in the occupation distribution, with a rise in clerical and sales occupations followed by a steep decline in farm operatives. In the low-skill group, which had displayed decreases in employment share throughout most of the twentieth century (also from 1920 to 1980), there were also some changes in the occupation distribution. The declining share of low-skill employment in the first half of the twentieth century can be traced back to the decline of farm laborers, while in the second half of the century both operatives and laborers in the manufacturing sector saw a steep decline in employment. On the other hand, service workers saw their employment levels almost double between 1920 and 2010. This occupational group is the main reason behind the fact that since the 1980s low-skill employment share has not been decreasing. This kind of job usually requires performing tasks that cannot be easily replaced due to how much they require personal interaction and the impossibility of offshoring them. However, the rising wage inequality might be associated with the fact that, even within low-skill occupations, this kind of occupation is one of the lowest paid.

According to Acemoglu and Autor (2011), during the decade of the 60s, real wages were rising regardless of the skill group. This can also be seen in every percentile of the earnings distribution, where both the 10^{th}, 50^{th}, and 90^{th} percentiles rose rapidly between the period of 1963 to 1973, when the logarithmic wage growth was around 20%. In the following decade, and largely due to the first oil shock, real wages fell at the low-skill groups, followed by a relatively stable period. The 10^{th} and 50^{th} percentiles were stagnant during the 70s, whilst the 90^{th} percentile started drifting away from the others, despite doing so more modestly than it would from this period onward.

Along the period of 1959-1979, the between-industry component was responsible for most of the growth in employment for high-skill workers. Technical, managerial and professional occupations, typically high-skill occupations, saw their employment increasing steeply due to their share in overall employment across every industry following the same positive trend. During the same period, the share of employment for production, craft, and operative occupations declined sharply, with around 65% of the change being explained by the between-industry component. Changes in earnings seemed to be almost completely explained by the educational attainment as well, sharing a monotonical relationship between these two variables. A higher educational level would guarantee every worker employment and a higher real wage level as well. However, as mentioned above, the premium for those who attained a higher level of education was modest during this period, as it would grow much more in the following decades.

It is during the 80s that wage levels started to reveal a significant disparity among educational levels, with real wages booming for highly educated workers, and falling for less-educated workers. Along this decade, the lower tail of the earnings distribution starts closing the gap with the median wage, bringing the U-shaped change of wages that characterizes the earnings distribution of nowadays. Beginning in this period, the explanatory power of educational attainment for earnings started to look less linear. Occupations' task content begins displaying increasing importance in explaining the evolution of earnings. Its explanatory power for earnings rose at such a pace that it overtook educational attainment in the 2000s. This shift in the indicators that explain the changes in earnings enhances the idea that occupations, along with its task composition, played an increasingly important role in the structure of the labor market both in terms of employment and earnings. Despite an attempt of introducing industry variables(such as industry dummies) in the equation, Acemoglu and Autor (2011) did not find any significant differences in the results, implying that changes in the industrial composition do not influence earnings by skill group whatsoever.

From 1979 through 2007, 75% of the growth in the employment share of high-skill workers was explained by within industry employment growth, with industries that employ these occupations intensively increasing their economical activity. The employment decline for clerical and administrative occupations was mostly explained by within industry employment declining as well. On the other hand, production, craft and operative occupations declined even more during this period than before 1980. However, within industry changes played a more significant role in explaining the changes in this group of occupations. As for service occupations, which are typically associated with low-skill labor, the rising share in employment is strongly caused by within industry changes as well. On a summary note, the fact that within-industry changes have favored both high-skill and low-skill employment at the cost of middle-skill employment, along with the pronounced significance that within-industry changes influenced employment in every occupation group, implies that job polarization is not a consequence of the shifts in industrial composition.

Acemoglu and Autor (2011) reveal many interesting details regarding the rising inequality in earnings by skill groups. From 1980 onward, most of the rising premium between workers with a college degree and those who do not have one stems from workers with a post-bachelor degree. The latter group has increased its real earnings steeply and monotonically. As for those who got a bachelor's degree, despite seeing their earnings rise monotonically as well, the magnitude of the increases has been fairly modest.

One concern regarding this sort of analysis is that measuring merely the real wage for less-educated workers as their only means of income is perhaps incomplete given the improvement of other forms of benefits such as healthcare. However, a study developed by Pierce (2001) proves that accounting for these benefits (by arranging a way of monetizing these compensations) does not yield major differences in comparison to the previous discoveries. In fact, the rise of this type of compensations has increased even more for high-skill workers than their real wages.

The result from both the trends defined above (sharp increase in real earnings for high-skill workers and decline in these for the rest) poses more than sufficient evidence that the structure of employment has changed in the past 30 years. Despite this, during the 1980s and 1990s, the dominant opinion among economic researchers was that technical change was skill-biased, favoring high-skill over middle-skill and the latter over low-skill. However, academic literature at the beginning of the 2000s came to realize that technology was actually replacing routine tasks rather than tasks that do not require a high level of schooling (mostly non-routine). These estimates clearly favored as well those who, not having necessarily an high-skill job, performed non-routine tasks such as nursing or housekeeping. As a result, the evidence was that both wage and employment structure was polarizing in most advanced economies.

However, the phenomenon of job polarization doesn't merely apply to the United States (US) labor market alone. Two decades years ago, Katz et al. (1999) gathered literature about this topic and realized that the majority of advanced economies went through a period of wage compression between the different skill groups and that after 1980 every country experienced a rise in differentials, with the magnitude of such rise differing from one economy to the other (Great Britain and the US had the biggest rises in earnings inequality). Goos et al. (2014) has studied the dynamics of the Western Europe labor market and found job polarization to be pervasive as well in Western Europe. The pattern is quite similar, with rising employment for high-paid professionals and managers and low-paid personal service workers, as well as declining employment for manufacturing workers and office clerks. Acemoglu and Autor (2011) found strikingly common patterns in terms of employment trends in the United States and the European Union. The authors computed the employment-weighted correlation between the US and EU changes in employment shares by each different occupation and found it to be 0.63, a remarkably positive correlation. Atkinson (2008) performed the kind of study for the period between 1980 and 2005 and concluded that the increased earnings inequality between the 50th and 90th percentiles was widespread among OECD economies. However, the inequality at the lower tail (between 10th and 50th percentile) was fairly heterogeneous from one economy to the other, varying in terms of the sign, significance, and even timing.

In terms of employment, there are some small differences from those seen at the earnings level. During the decade of the 80s, employment growth was quite monotonic, increasing for workers above the median level of skill and decreasing below the median. It was only on the turn at the decade that polarization in employment growth surged. At the higher percentiles of the skill structure, employment grew the most while the 10th percentile and below also grew but at a much more modest pace. On the other hand, the median skill level employment decreased moderately. However, from the decade of the 90s onward, the lower tail in the occupational structure boomed in terms of employment. At the same time, no other skill group was growing at such a disproportional rate. Almost every other percentile actually decreased in terms of employment, with the exception of the 90th percentile, where employment remained stable.

This trend was found in almost every other advanced economy besides the US, as described by Goos et al. (2009), which studied the employment structure of 16 European countries for the period of 1993-2006. Every country saw a decline in middle waged employment relative to other wage groups, averaging a decline in 8 percentage points between 1993 and 2006. In 11 of the 16 countries studied, low wage occupations grew as a share of employment. Besides this, in every single economy the low wage occupations grew relative to the medium wage occupations, averaging an increase of 10 percentage points.

Along the same period, high wage occupations were found to increase in 13 of 16 of the countries, averaging an increase of 6 percentage points. One can argue that job polarization since the 90s (arguably the 80s) has been pervasive throughout most advanced economies, not only the United States. In comparison with the periods of the 70s and the 60s (Unfortunately, due to the lack of data, it is impossible to establish a legitimate comparison using a larger time span), the weight that middle-skill jobs have on the employment structure declined massively. In 1979, the share of employment of middle-skill occupations such as sales, office and administrative workers, production workers and operatives combined would account for 57.3%. By the year of 2009, the same group of jobs had a share of 45.7% of the employment, having declined 3 percentage points from just the previous 2 years, when the share of employment was 48.6%. One other way of enhancing how important was the 80s as a transitioning period for the current situation of job polarization is computing the correlation of the occupational growth in every subsequent decade. While the correlation between occupational growth in 1989-1999 and 1999-2009 was 0.74, indicating nothing out of the ordinary occurred between those periods, the correlation between 1979-1989 and 1989-1999 was only of 0.53, implying that the way employment grew between these two decades was remarkably different. The way advanced economies' labor markets have been responding to such shocks in labor demand have some differences as well. Some economies seem to be experiencing higher inequality in terms of wages, while other economies experience a bigger difference in terms of employment. This can be partly explained by the wage-setting institutions. As explained by Katz et al. (1999), countries where unionization is weaker and wage-setting is decentralized (like the US and Great Britain) tend to experience a rise of wage inequality when labor demand reduces, as it was seen along the 1980s. On the other hand, economies like Germany and France, which have stronger unions and centralized wage-setting, tend to have a greater impact on employment levels. It seems that unionization may have a role as well on the way job polarization affects labor markets. It may not affect the magnitude of the polarization itself, but it does affect the way job polarization is experienced in labor markets with different characteristics.

2.3 *Job polarization and technical progress*

The main reason pointing towards technological progress hollowing out middle-skill jobs is the task content of occupations. While low-skill jobs and high-skill jobs often involve creative or social intelligence, most mid-skill occupations' tasks revolve around performing routine tasks. The routinization hypothesis has been associated with many different authors to job polarization. Jobs which consist intensively of routine tasks have been replaced due to technological progress.

Autor et al. (2003) concluded that job polarization was a result of the increase of productivity of the ICT (Information and Communication Technologies), as well as its decline in real prices. Nordhaus (2007) estimated that the real cost of performing a standardized set of computational tasks decreased on average 60-75% per year. The astonishing decline in the real price of computational processing provides more than sufficient incentive towards the substitution of expensive labor tasks for automated technologies. However, for any of these tasks to be automated (or routine), it depends on how thoroughly defined are the steps for performing a certain task, in order for a programmer to translate that task to a set of instructions which can be understood by a machine. This may also be one of the reasons why high-skill employment has experienced a considerable increase in demand as a result of technological progress.

Most tasks that are considered routine are performed in middle-skill cognitive or manual jobs. It is typical of middle-skill administrative, clerical and production jobs to consist of tasks that are guided by a set of well-defined procedures that can be programmed and consequently automated through computer software. The tasks of these occupations mostly revolve around organizing and storing information or performing manual routine tasks.

There are two broad categories of tasks that have been deemed as the most difficult to replace by means of computerization. The first, and mostly related to highly educated and analytically intensive jobs, includes tasks that involve problem solving capabilities, intuition, creativity or persuasion. This broad category, labeled as 'abstract', is heavily associated with professional, technical, and managerial occupations.

The second group, closely linked with low-skill personal service jobs, involve tasks that require situational adaptability, visual, and communication recognition, as well as personal interactions. This broad category is called non-routine manual tasks. At the core of this definition is any kind of task that requires adaptability and capacity of response to unexpected events. Examples of this group range from activities like driving a truck to food serving. However, take into account that most of these jobs do not require extensive formal education.

While technical progress enhances most occupations that are intensive in abstract tasks by empowering its workers with increasingly efficient tools, jobs intensive in manual non-routine manual tasks are neutral to the technological side. This characteristic has its strengths and weaknesses. Being neutral towards technological progress reduces significantly the risk of suffering from a negative shock in labor demand due to technical change. On the other hand, introducing new ways of making the job more efficient or improving job conditions is remarkably hard to accomplish due to the nature of these occupations.

Despite most literature pointing towards technical progress contributing towards job polarization, the pace and magnitude at which computerization occurs are not predictable. Until the adaptation of the labor market to these shocks is completed, employment will keep being replaced by machinery over an unspecified number of years. The adaptability of the labor market to such shocks will mainly depend on human capital growth in the upcoming years. With recent technological advancements, the choice of substituting labor by machinery still depends on both the costs of machinery and the response of wage levels to such shocks. Employment can be negatively affected by the direct displacement of workers whose tasks are mainly automatable. Nevertheless, there are three mechanisms that may counter this negative effect on aggregate employment.

The first is that the technology required to cause such labor-saving impact needs to be created in the first place, thus creating a demand for labor before even these technologies were created. Secondly, these technologies imply that the firms adopting it will have a boost on their competitiveness by lowering their production costs. Consequently, they will face higher demand for their product, thus creating a higher demand for other occupations within these firms. The third mechanism concerns the fact that these new technologies also complement some types of jobs, making them more productive. This can give rise to either higher wages or employment for these jobs. The more productive workers will then be able to consume even more, generating even more labor demand in the economy as a whole. A good example of this is the introduction of Automatic Teller Machine (ATM)'s in the banking sector. Bessen (2015) realized that, by reducing the cost of operating a bank branch, ATM's end up increasing the demand for bank tellers. Despite the number of tellers per branch being reduced by around 30% between 1988 and 2004, the number of bank branches increased by more than 40%. Since the routine tasks of bank tellers were now automatable, ICT advancements allowed for these workers to build a more efficient customer relationship. Ultimately, the banking sector realized that the true value of bank tellers was on building relationships with customers rather than processing payments or cashing cheques.

A more recent branch of academic research has surged with the focus on the risk of future automation completely depleting jobs. This is an increasingly heated debate topic given the disparity of results among different papers. Some of the difference between the results concerns the way each author perceive the composition of jobs.

As an example, Frey and Osborne (2017) which makes the assumption that every worker within the same occupation share the same task structure (occupation-based approach). Taking this into consideration, the authors yielded very concerning prospects of how many jobs are deemed to be automatable, with 47% of employment in the US being considered of high risk of being fully automated. On the other hand, studies that relax the assumption that workers in the same occupation share the same spectrum of tasks tend to yield much less exaggerated results (task-based approach). Arntz et al. (2016) relaxed the previous assumption and found that OECD countries have on average 9% of jobs considered to be fully automatable. The heterogeneity across jobs in different countries is also quite evident, with the share of automatable jobs in Korea reaching as low as 6%, while Austria's automatability of occupations reaching as high as 12%. This demonstrates how the assumption that workers sharing the same task composition within occupations is imperfect. The reasons behind this range from the differences in workplace organization to different levels of investment in automation technologies. Despite these differences, the research on this topic has a limitation. The data being used for the assessment of how automatable a job may be depends on a hand labeling performed by Machine Learning researchers back in 2013, where 70 occupations were labeled as either automatable or not and afterwards academics would use these labels to infer the degree of automatability for other occupations.

However, this approach has many constraints. The first is that the actual pace of technology is not accounted for as these labels only account for the current technology as of 2013. The second is that the economic trade-off between choosing to automate a certain task or job is not taken to account. The focus is mainly on whether current technology is able to automate the tasks or not and not so much whether the current wage level is higher than the cost of acquiring this technology. Another limitation concerns the adaptability of workers to new compositions of tasks implied in their current occupation. By having some tasks automated, workers can actually focus on the more relevant tasks (like non-routine tasks) of their occupation, increasing their productivity.

2.3 The effects of technical progress on labor demand

Despite the phenomenon of job polarization observed in the historical analysis, the effects of automation on labor demand come in various ways. Firstly, the adoption of technology that facilitates the automation of tasks allows for a displacement effect to take place. This shifts the allocation of resources away from labor, possibly reducing its share in the economy's production. It may result in the lowering of the ratio of labor productivity against capital since the pace at which new tasks are being created is not as fast as the pace at which they are being destroyed.

However, some of these advancements may stimulate the creation of new tasks that require labor as an input, making the latter more productive as a result, counteracting the displacement effect by increasing labor demand, share and wages. This is called the reinstatement effect. Additionally, productivity growth may compensate for the displacement of labor in some industries. Technological spillovers to industries more intensive in non-routine labor can lead to higher labor demand on aggregate as well, thus creating the possibility of labor reallocation to these industries, as well as increasing the income for such employment as a result of the increasing labor demand for those particular occupations. According to Acemoglu and Restrepo (2019), the reinstatement effect generates new tasks in which more skilled labor displays a comparative advantage. This goes in line with the theory of routine-biased technical change in the way that while more routine occupations are displaced as a result of automation, the high-skill labor becomes more productive. Nevertheless, the impact on aggregate labor is inconclusive, as several counteracting effects are operating when considering the effects of technological progress on aggregate labor.

Another case, although more common in less advanced economies, is the positive short-term effect that technological adoption can have in less advanced economies. As a result of the massive improvements in productivity, income may increase in the short term as a result of economical growth. This is the so-called productivity effect.

Through the development of a theoretical framework that modeled the way the introduction of new technologies affects labor, Acemoglu and Restrepo (2019) constructed a task-based model in which automation is adopted as an expansion to the set of tasks that can be performed using merely capital. This expansion is however different from the original set of tasks as it can replace labor in tasks that were previously exclusive to this input. However, and as describe above, there are other dynamics coming into the equation concerning the effects that technological adoption can have on labor. Consequently, the authors' framework also includes technological change that alters the task content of production in favor of labor by introducing new tasks to which labor has a competitive advantage, defined as labor-augmenting technologies. On the other hand, one should not dismiss the fact that this competitive advantage may be temporary as new forms of automating these tasks may arise in the long-term. These new technologies can also generate new tasks that render a competitive advantage for labor, making the introduction of new technology a catch-up process to the new demands of labor in a never ending process. The equilibrium is defined by the allocation of tasks between capital and labor being determined by the available technology as well as the endogenous decisions of firms between producing using capital or labor.

By adding to the model an extension that studies the way automation and creation of new tasks impact the income distribution, the inequality implications that stem from the technological change are accounted as well. The model is extended in a way such that high-skilled labor has a comparative advantage in the new tasks generated as a result of technological progress. This goes in line with the observed polarization in employment with the historical analysis form the literature review section.

The equilibrium in this model is determined by the way the available technology is composed, or how intensive it is in labor-augmenting technology, and the endogenous decisions of firms to produce using capital or labor. As expected, whenever the equilibrium intensity of tasks allocated to capital increases, the equilibrium wage declines as a result of the labor demand declining as well, with the assumption that labor demand is elastic.

Additionally, a major difference between this framework and the traditional models of directed technological change is that the change on a certain factor affects not only the spectrum of tasks performed by this factor but also stimulates the introduction of technologies that encourages firms to adopt this factor more intensively in its' production. As a result, if labor becomes more financially accessible to firms, not only will firms adopt it more intensively but also further technological advancements will be labor-augmenting, leading to a balanced growth path where labor will not be completely displaced.

Evidence from the framework does not suggest that either labor demand will completely vanish nor that the technology will always have a comparative advantage. Rather it suggests that if the source of growth in productivity will keep coming from automation and other technological advancements, the share of labor in output will continue to decline.

However, if the reinstatement effect compensates for the loss of jobs as a result of the automation, this trend may shift. The creation of new tasks is vital towards the increase in labor productivity and the resulting balance in the labor share of output. Not only are our innovation skills relevant for technology to advance in such a way that it generates these new tasks, but also is the supply of different skills, demographic indicators, institutional settings, and fiscal strategies.

3 THEORETICAL FRAMEWORK

Based on the framework developed by Costinot and Vogel (2010), this is an assignment model in which a continuum of factors, workers in this case, are employed to produce a continuum of goods, defined as tasks. Markets are perfectly competitive and tasks are combined to output an unique final good through a Dixit-Stiglitz production function. Workers are allocated across tasks based on their comparative advantage in an equilibrium.

3.1 Environment

The economy is populated by a continuum of workers with skills $s \in \mathbb{R}$. *N(s)* is the inelastic supply of workers with skill *s* and *S* is the economy's set of skills. Note that $N(s) \geq 0$ and $S \equiv \{s \in \mathbb{R} | N(s) \geq 0\}$. The economy only produces one final good that requires a continuum of intermediate tasks indexed by their skill intensity $\sigma \in \mathbb{R}$. In order to produce every sort of task, heterogeneous skills among workers are required. The Dixit-Stiglitz production function of the final good output is the following:

$$Y = \left\{ \int_{\sigma \in \Sigma} B(\sigma)[X(\sigma)]^{(\varepsilon-1)/\varepsilon} d\sigma \right\}^{\varepsilon/(\varepsilon-1)} \tag{1}$$

where $B(\sigma) \geq 0$ is an exogenous technological parameter which indicates the productivity of task σ , $X(\sigma) \geq 0$ is the endogenous output from task σ, $0 < \varepsilon < \infty$ is the constant elasticity of substitution between tasks. $\Sigma \equiv \{\sigma \in \mathbb{R} | B(\sigma) > 0\}$ is the economy's global set of tasks. Technologies are restricted to the set of tasks $\Sigma = [\underline{\sigma}, \overline{\sigma}]$ despite the possibility of B stemming from different sources. V and B are also assumed to be continuous functions.

Workers are perfect substitutes in the production of tasks. However their productivity level $A(s, \sigma) > 0$ is different. The output of task σ is defined as

$$X(\sigma) = \int_{s \in S} A(s, \sigma) L(s, \sigma) ds \tag{2}$$

where $L(s, \sigma)$ is the endogenous labor with skill s performing task σ. Since $A(s, \sigma) > 0$ and assuming that it is twice differentiable and log-supermodular ($lnA/\partial s \partial \sigma > 0$):

$$A(s', \sigma') A(s, \sigma) > A(s, \sigma') A(s', \sigma) \text{ for all } s' > s \text{ and } \sigma' > \sigma \tag{3}$$

This property may also be interpreted as high-skill workers having a comparative advantage in tasks more intensive in high skills, meaning that higher s is assigned to the production of higher σ.

Since all goods are being produced by a large number of identical firms, markets are perfectly competitive. As firms are price-taking, total profits for the final good are derived from

$$\Pi = \left\{ \int_{\sigma \in \Sigma} B(\sigma)[X(\sigma)]^{(\varepsilon-1)/\varepsilon} d\sigma \right\}^{\varepsilon/(\varepsilon-1)} - \int_{\sigma \in \Sigma} p(\sigma) X(\sigma) d\sigma \tag{4}$$

where $p(\sigma) > 0$ is the price of task σ. Total profits for intermediate good σ are

$$\Pi(\sigma) = \int_{s \in S} [p(\sigma) A(s, \sigma) - \omega(s)] L(s, \sigma) ds \tag{5}$$

where $\omega(s) > 0$ is the wage for a worker with skill s.

3.2 Competitive equilibrium

Since all markets are perfectly competitive, firms maximize their profits and markets clear in a competitive equilibrium. Therefore, the supply of workers is entirely allocated. Total income is given by

$$I \equiv \int_{s \in S} \omega(s) N(s) ds \tag{6}$$

Profit maximization by the final good producers is conditioned by the optimal production of each task σ

$$X^*(\sigma) = I[p(\sigma)/B(\sigma)]^{-\varepsilon} \text{ for all } \sigma \in \Sigma \tag{7}$$

where equation (7) represents the first order condition for the final good producers' problem.

For intermediate goods, profit maximization by the producers is defined by

$$p(\sigma)A(s,\sigma) - \omega(s) = 0 \text{ for all } s \in S \text{ such that } L(s,\sigma) > 0 \tag{8}$$

where equation (8) represent the first order condition for the intermediate producers' problem. For any given non-negative amount of labor, there is no profit as the intermediate goods market is a perfectly competitive market. The final good and labor market clearance is conditioned by

$$\begin{aligned} X(\sigma) &= \int_{s\in S} A(s,\sigma)L(s,\sigma)ds \text{ for all } \sigma \in \Sigma \\ N(s) &= \int_{\sigma\in\Sigma} L(s,\sigma)d\sigma \text{ for all } s \in S \end{aligned} \tag{9}$$

Thus, a competitive equilibrium can be defined as the result of a set of functions $Y : \Sigma \to \mathbb{R}^+$, $L : S \times \Sigma \to \mathbb{R}^+$, $p : \Sigma \to \mathbb{R}^+$, and $\omega : S \to \mathbb{R}^+$ such that conditions (7) - (9) hold.

In this competitive equilibrium, there also exists a continuous and strictly increasing matching function $M : S \to \Sigma$ such that (i) $L(s,\sigma) > 0$ if and only if $M(s) = \sigma$, and (ii) $M(\underline{s}) = \underline{\sigma}$ and $M(\overline{s}) = \overline{\sigma}$.

Due to markets being perfectly competitive and factors of production perfect substitutes in every task, the output is entirely allocated to workers' income

$$Y = I \tag{10}$$

It is the comparative advantage that determines factor allocation. Since A is strictly log-supermodular (see equation (3)), high-skill workers have a comparative advantage in tasks intensive in high skills. This proves the monotonicity of the matching function M.

In order to be in a competitive equilibrium, the matching function M and wage schedule ω is defined by the following properties:

$$\frac{dM}{ds} = \frac{A[s, M(s)]N(s)}{I \times \{p[M(s)]/B[M(s)]\}^{-\epsilon}} \tag{11}$$

$$\frac{d\ln\omega(s)}{ds} = \frac{\partial \ln A[s, M(s)]}{\partial s} \tag{12}$$

with $M(\underline{s}) = \underline{\sigma}$, $M(\overline{s}) = \overline{\sigma}$ and $p[M(s)] = \omega(s)/A[s, M(s)]$.

These two constraints imply that a system of ordinary differential equations yields the solution for the two key endogenous variables in the model, the matching function M and the wage schedule ω. Through equation (11), one can see that the market clearing condition determines the matching function. Equation (12) demonstrates how profit maximization determines the wage schedule. Differences in relative productivity will reflect in differences in relative wages as well. After computing M and ω, Y and p can be computed by substituting them using equations (7) and (8).

3.3 Comparative statics

Having knowledge about the competitive equilibrium obtained from the previous section, the effects of a change in factor demand will now be analyzed. More specifically, the case of how an exogenous change in B affects the matching function M. Equation (12) gives an idea of how the wage schedule ω is influenced by this exogenous shock.

A shift in B, from B to B', is introduced such that:

$$\begin{gathered}\text{(i) } B \succeq B' \text{ for all } \sigma < \hat{\sigma} \\ \text{(ii) } B' \succeq B \text{ for all } \sigma \geq \hat{\sigma}, \text{ with } \hat{\sigma} \in \Sigma\end{gathered} \tag{13}$$

By shifting from B to B', the relative demand for tasks intensive in low skills increases within the range of $\sigma < \hat{\sigma}$. The inverse occurs for tasks intensive in high-skills within the range $\sigma \geq \hat{\sigma}$. This relative change in demand may be a consequence of the introduction of new tasks in the economy.

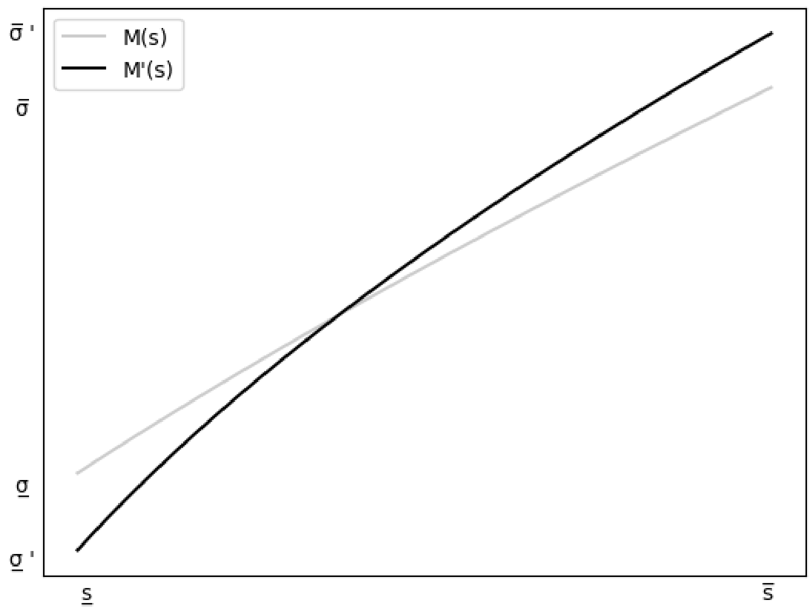

FIGURE 1: Extreme-biased technological change and matching

Source : Costinot and Vogel (2010)

Formally, B' is extremely biased relative to B if condition (13) holds. Let M and M' denote the respective matching functions of B and B'. There exists a skill level $s^* \in S$ such that $M(s) \geq M'(s)$ for every $s \in [\underline{s}, s^*]$ and $M(s) \leq M'(s)$ for every $s \in [s^*, \overline{s}]$. The skill level s^* can be found at the intersection between $M(s)$ and $M'(s)$ in Figure 1.

The shift from B to B' reallocates workers from tasks at the intermediate part of the spectrum of σ toward tasks at the extremes of the spectrum of σ. This reallocation can also be deemed as wage polarization. Relative wages will be:

$$\frac{\omega'(s')}{\omega'(s)} \leq 1 \text{ for all } \underline{s} \leq s < s' \leq s^*$$
$$\frac{\omega'(s')}{\omega'(s)} \geq 1 \text{ for all } s^* \leq s < s' \leq \overline{s} \tag{14}$$

Equation (14) implies an income convergence between the low-skilled workers and an higher income disparity among the higher-skilled workers, resulting in a more disperse income distribution. This is perceived as extreme-biased technological change resulting in wage polarization.

4 MEASURING ICT USE AND ROUTINENESS AT WORK

This section aims to provide the reader with a comprehensive explanation about the way data was collected and other techniques that were applied in order to collect the set of indexes that are going to be used throughout our empirical analyses, namely the Routine Task Intensity (RTI) and the ICT use index.

4.1 Data Sources

In order to perform the empirical analysis that can be found further below, the data that was used comes from the OECD's PIAAC. This Programme contains surveys conducted during 2011 and 2012 that contain respondents coming from 22 participating countries. The 22 participating economies are Austria, Belgium, Canada, Czech Republic, Germany, Denmark, Spain, Estonia, Finland, France, Great Britain, Ireland, Italy, Japan, South Korea, Netherlands, Norway, Poland, Russian Federation, Slovak Republic, Sweden, and the United States. The complete database contains around 160,000 respondents aged from 16 to 65. Within this survey, there can be found information about the individual's characteristics, formal education and training, current work status and its characteristics at both the current and the last occupation. This survey also contains an assessment of each respondent's skills in terms of both numeracy, literacy and problem-solving skills, as well as the intensity at which technology is used at work. Some of the data that was gathered can be broadly categorized in four different groups of variables: The individual variables, which contain gender, age and educational level; cognitive skills variables, containing a numeracy and literacy skill assessment of the workers; job characteristics which are composed by a set of workplace characteristics such as the firm's economic sector, its size and whether or not the worker has received on-the-job training; the occupation, represented by the respondent's occupation code presented at the level 1 International Standard Classification of Occupations (ISCO) code and lastly the monthly earnings including bonuses for wage and salary earners in $US at the Purchasing Power Parity.

Additionally, another set of variables was taken into account as well. These variables were retrieved in order to construct the above mentioned indexes of routineness at work (RTI) and technological adoption at the workplace (ICT Use). These indexes result from a statistical procedure called Principle Component Analysis. Both indexes are the result of an orthogonal transformation of other variables taken from the PIAAC survey. The reason behind the transformation of such variables in order to generate each of the indexes is the possible correlation between each of them. By aggregating these variables using the Principal Component Analysis (PCA) we ensure that the resulting index is not influenced by the possible correlation between each variable.

Following Abdi and Williams (2010), the purpose of the PCA is to extract the relevant information from a set of inter-correlated dependent variables and to produce a new set of orthogonal variables called principal components. The first component that results from these orthogonal variables will operate as the reference for the RTI and ICT indexes.

The methodology for such indexes was based on De La Rica and Gortazar (2016), with a few additional variables. The RTI index from De La Rica and Gortazar (2016) was by itself based on the construction from Autor (2013). See Appendix A for a detailed explanation of the PCA.

Table II displays the variables used for the construction of both indexes.

In the ICT index, five questionnaire answers are taken into consideration. Within these variables are the use of the internet for issues related to work, use of the internet to conduct transactions online, the use of spreadsheet software such as excel, the use of a programming language and the level of computer use.

Every variable in this index is a response that is given in terms of frequency, ranging from 1 ("Never") to 5 ("Every day"), with the exception of the level of computer use, which can have three different answers: straightforward, moderate, and complex.

As for the RTI case, the proceeding is slightly different. The same statistical method for dimensionality reduction called Principal Component Analysis is applied in order to yield the index of routine task content at the workplace. The first component of the Principal Component Analysis was computed for the Abstract non-routine, Manual non-routine and routine activities. However, it is the subtraction between the first component from each the three principal components that yield the final index.

In order to compute the Routine Task Intensity index, the method proposed by Autor (2013) will be followed. The index is constructed in the following way :

$$RTI_i = lnR_i - lnA_i - lnM_i \tag{15}$$

, where R_i, A_i and M_i stand for the Routine, Abstract and Manual task indexes respectively. However, given that our indexes are already computed in a standardized form, the logs are not included in the computation of the RTI index, following the same approach as De La Rica and Gortazar (2016). The reasoning behind this alternative approach is to ensure the positive signal of every task measure. Hence, our measure of the RTI is :

$$RTI_i = R_i - A_i - M_i \tag{16}$$

The Routine indicator was computed using the following variables: Change sequence of task (frequency); Change how to do work (frequency); Change of the speed of work (frequency); Change of working hours (frequency); Learn work-related things from co-workers; Learning by doing from tasks performed; Keeping up to date with new products/services and Hand/Finger skill accuracy.

As for the Abstract indicator, the variables taken into account were the following: Read Diagrams, Maps or Schematics (frequency); Write Reports (frequency); Persuading/Influencing people (frequency); Negotiating with people (frequency); Faced complex problems which last more than 30 minutes (frequency). Table II gives a summary of all the variables used for the construction of both the ICT Use and the RTI index.

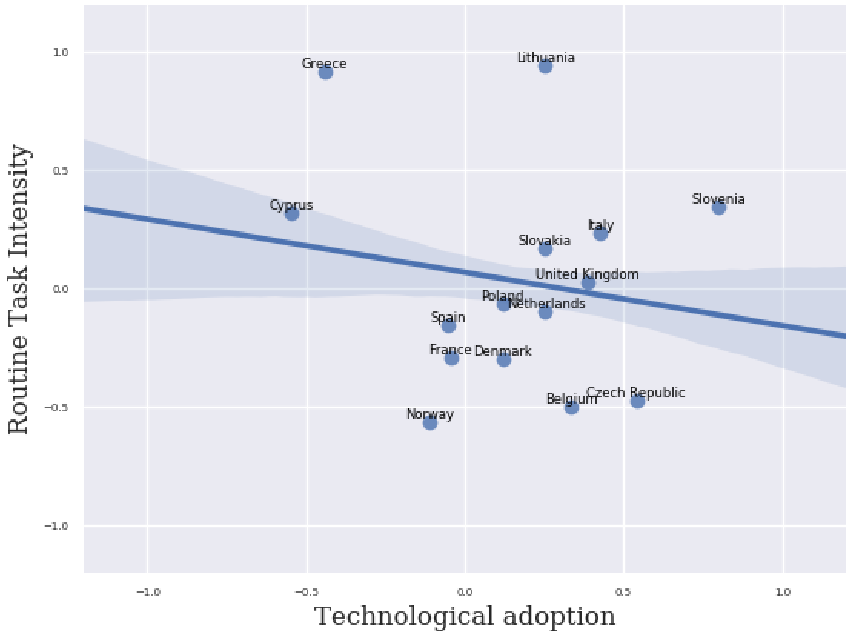

FIGURE 2: Routine Task Intensity and ICT use by country

Source : Author's own calculations

Figure 2 displays the relationship between both indexes for each country. For each point in the graph, there is the average Routine Task Intensity and technological adoption at work level of each country in our data. The negative relationship between technological adoption and Routine Task Intensity at work is quite evident. However, Figure 2 merely displays a fitted regression using the ICT index as the only explanatory variable, thus ignoring several other control variables that might be deemed as relevant to explain the Routine Task Intensity at work, possibly incurring in the omitted variable bias. Nonetheless, it is worth noting the negative relationship between the two indexes. This implies that economies with more advanced technologies are the ones with fewer routine occupations in their labor structure.

FIGURE 3: Routine Task Intensity by level of education (ISCED 1997 levels)

Source : Author's own calculations

Through the introduction of educational attainment as a proxy for skill level, a relationship between Routine Task Intensity at work and skills can be attained. Figure 3 depicts the relationship between skills (using educational level at International Standard Classification of Education (ISCED) 1997 levels) and the routine intensity extracted from our index. For each educational level, the average RTI is presented. Despite the residually positive routine intensity at the low skill occupations, the middle-skill are the most routine occupations by a fairly large margin. As expected, the least routine occupations are high-skill (associated with tertiary education). These insights retrieved from Figure 3 go in line with the Routine Biased Technical Change Theory, which states that the occupations more routine intense in their task content are those at middle of the skill spectrum.

5 EMPIRICAL ANALYSIS

5.1 ICT adoption and Routine intensity of tasks at work

In this section, we assess the first implication from Autor and Dorn (2013) which states that, as a consequence of a lower relative price of computer capital, a greater adoption of ICT at work will shift labor away from routine task intensive occupations. A pooled linear model with country fixed-effects for worker i residing in country j, where $j = 1....22$ will be utilized. Hence, the model is presented in the following way:

$$RTI_{ij} = \beta_0 + \sum_m \beta_{1m} X_{ijm}^{Ind} + \sum_n \beta_{2n} X_{ijn}^{Skill} + \sum_p \beta_{3p} X_{ijp}^{Job} + \beta_4 X_{ij}^{Occ} + \beta_5 X_{ij}^{ICT} + \delta_j + \varepsilon_{ij} \tag{17}$$

, where X_{ijm}^{Ind} represents the set of individual characteristics that include age, gender and education level. X_{ijn}^{Skill} is the worker's literacy and numeracy cognitive skills index. X_{ijp}^{Job} contains information about the characteristics of the workplace. These include whether or not on-the-job training exists, the firm size, its economic sector and whether it's a public or private firm. X_{ij}^{Occ} is the worker's occupation given at the ISCO level-1 code. X_{ij}^{ICT} represent the worker's index of ICT use at work.

The country fixed-effects will account for the differences between each country that cannot be explained through the model. These effects are included in the model as δ_j. Finally, ε_{ij} stands for the model's error term. The difference between the fixed effects estimator and the random effects estimator is that δ_j does not necessarily need to be independent of the explanatory variables. However the same does not hold for ε_{ij}. where every term of the equation represents the contribution to the explained effect of the difference between routine and non-routine workers for each set of explanatory covariates.

Firstly, the equation (17) will be estimated using only the country fixed-effects. The latter can be deemed as the raw or unconditional cross-country differentials with respect to the RTI index. By including the ICT use index afterwards, we compute the unconditional effect of the ICT use at work on the RTI index.

On a second stage, we include the Individual characteristics, Cognitive skills, Job characteristics and Occupation set of variables as control variables. A more detailed explanation about each variable from these sets of control variables can be found in the data section above. Having a more complete specification of the regression explaining the RTI index allows us to take a step further and analyze the effect of ICT use on RTI taking into consideration other characteristics associated with every individual worker, thus leading us to a more complete assessment of the effect of ICT use on the RTI index.

By including the sets of control variables in equation (17), thus studying the conditional differences between these workers. This approach allows us to understand the magnitude of the explanatory power that the ICT use can have on the RTI difference between these workers. Given these sets of control variables, if the ICT use at work remains significant at explaining RTI, one can confirm Autor (2013) implication that a stronger adoption of technology at work leads to a shift of employment away from routine intensive work with a strong degree of certainty.

5.2 ICT adoption at work and wage polarization

In this section, an analysis of the effect of ICT use on the wage structure will be performed through a method called the Oaxaca-Blinder linear decomposition. The OB decomposition is often used as a way to study labor-market differences by two different groups. An example of this division can be the gender, ethnic group or income group. In order to do so, a counterfactual is built based on the mean differences between the two groups. After computing the wage differential between the two groups, the latter is split into two parts. The first is the explained part of the differential, where the independent variables of the model are taken into account to explain the difference between the two groups. This is also called the composition effect. There is also an unexplained part of the differences, often called the wage structure effect. This part of the equation accounts for differences between the two groups that are not explained by the independent variables. Nonetheless, this part should not be deemed as the amount of differential between the two groups that is solely based on discrimination as there may be other explanatory variables that are not being considered and actually have an effect on the differential. If the latter were being taken into account, they would have been a part of the composition effect.

Let's start off by assuming that the wage equation

$$W_g = X\beta_g + \varepsilon_g \qquad \text{for } g = A, B$$

is linear, distinguishable between its observed and unobserved characteristics, and $E[\varepsilon_g|X] = 0$. Being $D_B = 1$ the indicator of group B membership and accounting for the expectations over X, the total difference in the wage gap Δ^{μ}_{O} may be expressed as

$$\Delta^{\mu}_{O} = E[W_B|D_B = 1] - E[W_B|D_B = 0]$$
$$= E[E(W_B|X, D_B = 1)|D_B = 1] - E[E(W_A|X, D_B = 0)|D_B = 0]$$
$$= (E[X|D_B = 1]\beta_B + E[\varepsilon_B|D_B = 1]) - (E[X|D_B = 0]\beta_A + E[\varepsilon_A|D_B = 0])$$

with $E[\varepsilon_B|D_B = 1]) = E[\varepsilon_A|D_B = 0]) = 0$. If we compute the average counterfactual wage of workers in group B under the wage structure of group $A(E[X|D_B = 1]\beta_A)$, the overall mean wage gap will be:

$$\Delta^{\mu}_{O} = (E[X|D_B = 1]\beta_B - E[\varepsilon_B|D_B = 1])\beta_A + E[\varepsilon_B|D_B = 1])\beta_A - E[\varepsilon_B|D_B = 0])\beta_A = E[X|D_B = 1](\beta_B - \beta_A) + (E[X|D_B = 1] - E[X|D_B = 0])\beta_A$$

If we substitute $E[X|D_B = d]$, being $d = 0, 1$, with the sample averages $\overline{X}_g$:

$$\begin{aligned} \Delta^{\mu}_{O} &= \overline{X}_B\widehat{\beta}_B - \overline{X}_B\widehat{\beta}_A + \overline{X}_B\widehat{\beta}_A - \overline{X}_A\widehat{\beta}_A \\ &= \overline{X}_B(\widehat{\beta}_B - \widehat{\beta}_A) + (\overline{X}_B - \overline{X}_A)\widehat{\beta}_A \\ &= \Delta^{\mu}_{OS} + \Delta^{\mu}_{OX} \end{aligned} \tag{18}$$

The first term in the equation above (Δ^{μ}_{OS}) is denoted as the wage structure effect. The wage structure effect can also be deemed as the unexplained part of the wage differentials between groups A and B. The second term of the above equation (Δ^{μ}_{OX}), which is the so-called composition effect or the differentials in wage that can be explained by the differences in the control variables between the two groups.

In order to compare differences in wages between routine and non-routine workers, we arbitrarily created two groups based on our RTI index, each representing the routine and non-routine workers. By doing this, ensuring that it is possible to assess the decomposition of the wage gap between these two groups. In other words, it is being evaluated how significant is the effect that the index of technology adoption at work can have on wage gap between routine and non-routine workers, taking into account the aforementioned set of control variables. Thus, one may test the implication by Autor (2013) in which a greater technological adoption at work will lead to wage increases for non-routine workers, as routine workers are either forced to displace from their current occupation or experience wage reductions as the price of computer capital decreases and its productivity increases. Given that the RTI index is in the standardized form, two groups (routine and non-routine workers) are formed in which one has a positive RTI index and the other a negative RTI index. Our variable of interest is the average monthly wages and we use the same set of control variables described in the previous empirical analysis.

Being the focus of this analysis the effect of ICT use in wage differentials, the wage structural effect is ignored since it can only inform us about the presence of discrimination between the two groups when accounting for wages. The intent is not to study whether there is a "natural" pay gap between routine and non-routine workers but rather to seek some determinants of the latter.

Hence, the composition effect can be written in the following way :

$$\begin{aligned}\hat{\Delta}_X^{\mu} = (\overline{X}_B^{Ind} - \overline{X}_A^{Ind})\hat{\beta}_1 + (\overline{X}_B^{Cog} - \overline{X}_A^{Cog})\hat{\beta}_2 \\ +(\overline{X}_B^{Job} - \overline{X}_A^{Job})\hat{\beta}_3 + (\overline{X}_B^{Occ} - \overline{X}_A^{Occ})\hat{\beta}_4 \\ +(\overline{X}_B^{ICT} - \overline{X}_A^{ICT})\hat{\beta}_5 + \varepsilon\end{aligned} \tag{19}$$

where $(\overline{X}_B^{ICT} - \overline{X}_A^{ICT})\hat{\beta}_5$ is the contribution of the mean differences in ICT use between routine (A) and non-routine workers (B) to the mean difference in wage between these two groups.

Figure 4 displays the distributions of earnings for both groups. As expected, the left tail of the distribution displays small differences between both groups, as some low-skill occupations are still deemed as routine. As we get closer to the middle of both distributions, we can see a higher frequency of routine workers, indicating that middle-skill workers are indeed those with higher routine task indexes. Once we get to the higher wages part of the distribution, we can see more and more non-routine workers, which is also something to expect, thus confirming that high-skill workers are indeed non-routine.

6 EMPIRICAL FINDINGS

6.1 Technological adoption and Routineness at work

This section provides an analysis of the relationship between technological adoption at work and the intensity of routine tasks. In order to do so, an implementation of a pooled model using the fixed effects estimator will be applied. Firstly, this model will

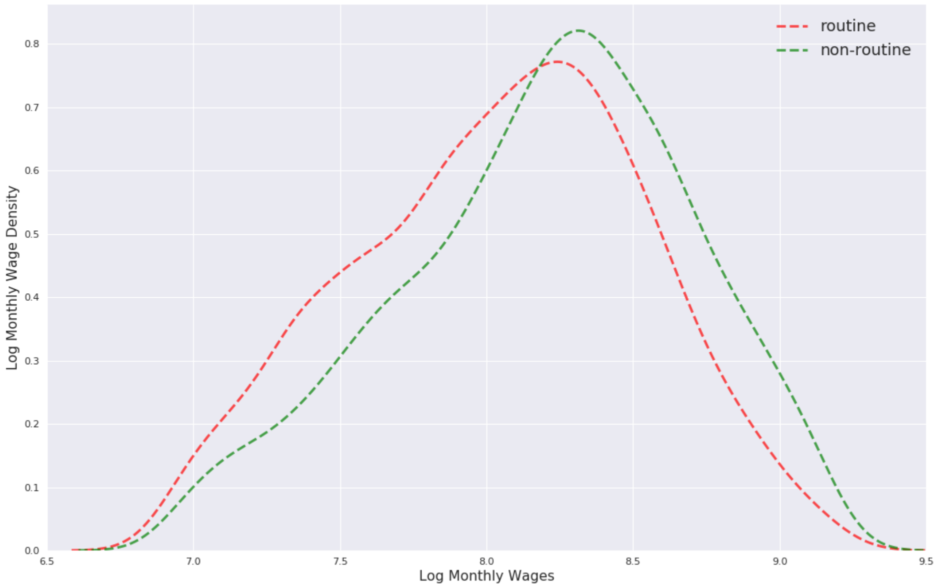

FIGURE 4: Log Monthly Wage density by routine and non-routine workers

Source : Author's own calculations

merely include the fixed effects (in this case will be the worker's country) and the variable of interest (the ICT Use index). On a second stage, other variables of control will be included progressively. In other words, each iteration of this model will include a new set of variables. Namely, those variables included in the individual characteristics, cognitive skills and job characteristics groups, and the occupation at the 1-digit ISCO 2008 code.

Table IV displays the unconditional cross-country differences before and after including the ICT use at work.

As the ICT use index is introduced, the coefficient of determination(R^2) increases. This means that out of total the variance in the dependent variable, the portion that is explained by the independent variables increases by 3 percentual points.

Additionally, the ICT use index coefficient displays a statistically significant impact on the RTI index. The resulting coefficient from the fixed-effects estimation is negative as well. A shift from labor demand towards occupations adopting technology more intensively will therefore result in fewer routine occupations, implied by Autor (2013), as an economy where technological adoption at work is widespread is less propense to being intensive in routine-intensive labor.

On a second analysis, a set of control variables that cover characteristics such as personal characteristics from the worker, their cognitive skills, workplace characteristics and occupation code is introduced. Table V contains the coefficients, significance levels, and standard deviations from equation (17). This regression includes not only the country fixed-effects and the index of ICT use at work but also a set of control variables.

The estimates of this regression go along with the first implication from Autor (2013). The coefficient for ICT use after controlling for these variables maintains its negativeness, confirming that a higher adoption of technology at work does indeed lead to a lower index routine content of tasks at work.

Additionally, ICT use displays statistical significance when estimating the RTI index at the 1 percent level of significance. Therefore, higher degrees of technological adoption at work are indeed associated with having a job considered as non-routine, as it was implied by Autor (2013). The model results show that indeed jobs in which technology has already been introduced are the ones considered less routine as the tasks in these occupations that were deemed repetitive have already been displaced.

As for control variables, every variable within the individual characteristics displays a negative impact on the RTI index. Given that this variable group includes the individual's age, perhaps this is the most surprising insight, meaning that at a higher age, workers do indeed tend to have tasks with less routine content rather than at a younger age. Also, every variable at this group has a statistically significant impact on routineness at work when the whole set of control variables is taken into account.

Within the cognitive skills variable group, there is the index of numeracy skills at work, which includes the use of problem solving skills that involve mathematical computation, which displays a positive and significant coefficient.

Unfortunately, the interpretation of certain variables, such as occupation and economic sector, becomes a cumbersome task since these consist of merely an occupation code and therefore having a positive or negative sign has no possible interpretative meaning. However they are included as a way of capturing within-occupation and within-sector dynamics.

Nevertheless, within the job characteristics variable group, there are still the firm size and on-the-job training. While on-the-job training has a negative but not statistically significant impact on the routine intensity index, the same applies to the firm size with the exception that the latter displays significance at the 5% level of significance. The lack of statistical significance associated with on-the-job training in terms of explaining the routine content of work seems surprising at first. However, a possible explanation for this may be that high-skill occupations tend to be associated with those that require a higher degree of education. The human capital required to perform such occupations might have been already accumulated from past formal education and therefore less training for the job is need.

6.2 Technological adoption and Wage polarization

In this section, we evaluate the Autor and Dorn (2013) implication which states that the higher the degree of technology adoption, the greater are wages for both high-skill Abstract and low-skill Manual workers, i.e non-routine workers.

Table VI shows the Oaxaca-Blinder decomposition approach estimates. The focal point of the estimates from this table is $\hat{\beta}_5$, the coefficient that concerns the way economies with higher degrees of technological adoption at work differ between routine and non-routine occupations in terms of earnings. The positive coefficient indicates that the higher the differences in ICT use, the higher the differences in earnings between routine and non-routine workers. Additionally, its impact on the earnings difference is statistically significant at the 1 percent significance level. Therefore, one may conclude that the higher the degree of technology adoption, the greater are wages for non-routine workers, as it was proposed by the Autor and Dorn (2013) implication. This also proves the existence of the displacement effect as proposed by Acemoglu and Restrepo (2019) since routine-intensive labor is being replaced as technology progresses. As for other explanatory variables, every coefficient indicated statistical significance at the 1 percent level (with the exception of the numeracy skill index, which has a 5 percent level of significance). It is the signal of the coefficient that varies from one independent variable to another. Within the individual characteristics, we have the gender, age and education level. The gender coefficient is -0.3002, indicating that gender has a negative impact on the difference between routine and non-routine workers in terms of income. As for Age, the coefficient is 0.0853, meaning that higher age differences display a positive impact on the differences between the two groups in terms of income. The educational attainment displays a positive coefficient as well. A possible explanation for this is the fact that more advanced economies display not only higher levels of educational attainment but also higher levels of technological progress. Therefore it is expected that an economy in which there is a higher degree of educational attainment, one can also find higher wage differences as the demand for routine labor is much lower. Within the cognitive skills variables, there are the numeracy and literacy indexes. Their coefficients are 0.0111 and -0.0019. A higher numeracy skill score enhances the wage difference between routine and non-routine workers. This goes in line with the same logic applied for the educational level variable. This index is also more associated with occupations that require non-routine capabilities. Surprisingly, the same does not apply to the literacy score as this index displays a negative coefficient, implying a higher convergence in income for higher levels of literacy. The Job characteristics variable group consists of the economic sector of the individual's firm, its size in terms of the number of workers and whether or not the individual had some on-the-job training. The economic sector variable is merely a code. Any sort of interpretation from the coefficient would not make sense. The same logic applies to the Occupation variable, which is a four-digit code. The firm size coefficient is 0.1034. Hence, the higher the average size of firms in an economy, the higher their income difference as well. Surprisingly, the coefficient for having on-the-job training is negative (-0.0945). This may be interpreted as the convergence between the two groups in terms of income given a bigger difference in terms of the proportion of on-the-job training within the groups of routine and non-routine workers.

Figure 5 depicts the contribution of the composition effect (or explained effect) to total wage gap ratio. This is the ratio between the explained part, or that of the independent variables, and the total gap in wages between routine and non-routine workers. Notice how the introduction of ICT use into the model generated an increase of about 10 percentual points from the previous model which included occupation, job characteristics, cognitive skills and individual characteristics variables. It is also worth mentioning that the inclusion of independent variables led in general to a reduction in the weight of the wage structural effect (with the exception of the job characteristics), meaning that almost every variable group included increased the share of the composition effect on total wage gap.

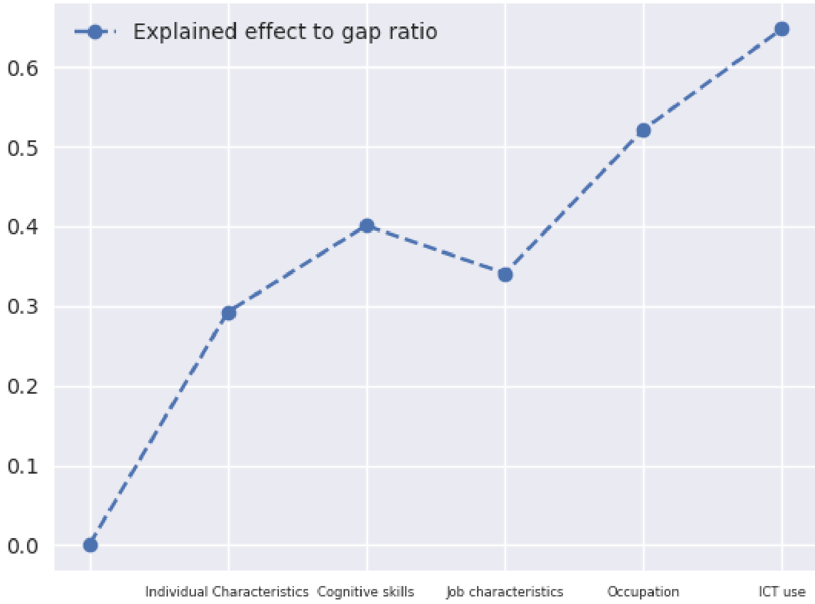

FIGURE 5: Ratio of wage composition effect to total gap

Source : Author's own calculations

7 CONCLUSION

This dissertation addresses the way the labor market is affected by technological progress. The research is centered around the phenomena of job polarization, in which routine intensive labor is being displaced as a result of automation. The estimation results from the empirical analyses performed show that our results are consistent with the implications stated by Autor (2013). Two indexes were developed so that these hypotheses could be tested. One is the Routine Task Intensity (RTI), which will measure how routine is each individual worker's occupation based on the tasks being performed. The other index is the Information and Communication Technology (ICT) index. This index will estimate the intensity of technological adoption at the workplace. The fixed-effects regression results confirm that higher technological adoption at work is associated with less routine intense labor. The Oaxaca-Blinder decomposition demonstrates that economies with higher technological adoption at work also experience more pronounced earnings disparity between routine and non-routine groups of workers. Such results are consistent with the notion of the displacement effect given by Acemoglu and Restrepo (2019). The labor demand for routine labor is in fact smaller when more technologically advanced economies. As a results wages diminish for this group of workers, causing the phenomena of wage polarization. The data was gathered from the OECD's PIAAC. Due to the cross-sectional nature of the dataset, analyzing the time dynamics was not possible. It could be of great value to study how other effects, such as the standardization effect, can influence the marginal productivity of technological adoption for high-skill labor. Another interesting topic would be to evaluate whether the standardization effect may restore income inequality in the long-run, and if so, what are the determinants that influence any of these effects. Another aspect that should be concerned is the possibility that the reinstatement effect compensates for the loss of jobs on the aggregate. The creation of new tasks is vital towards the increase in labor productivity and the resulting balance in the labor share of output. If the standardization effect does not reduce inequality in the long-term, educational attainment and the supply of high-skill labor can compensate for the displacement of routine labor. Mind however that other variables such as demographic indicators, institutional settings and fiscal strategies may be relevant to address the pace at which both the routine labor displacement effect and the productivity increases on the non-routine labor known as reinstatement effect.

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8 Appendix A

8.1 Principal Component Analysis

The PCA consists of an orthogonal transformation of a set of possibly correlated variables into a new set of uncorrelated variables named principal components.

The data to be analyzed by PCA comprises of *I* observations described by *J* variables and it is represented by the $I \times J$ matrix $\boldsymbol{X}$, whose generic element is $x_{i,j}$. The matrix $\boldsymbol{X}$ has a rank *L* where $L \leq$ min $\{I, J\}$.

Before computing the Principal Component Analysis of $\boldsymbol{X}$, the Singular Value Decomposition must be defined first. In simpler terms, the Singular Value Decomposition (SVD) is an expansion of the original data in a way such that the covariance matrix is diagonal.

Its computation consists of finding the eigenvalues and eigenvectors of $\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}}$ and $\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X}$. These matrices have very convenient properties such as being symmetrical and square. Additionally their eigenvalues are zero, making them either positive semidefinite or positive definite. The fact that they are symmetric allows its eigenvectors to be orthonormal. Having positive or at least neutral eigenvalues allows for their singular values to be the square roots of the eigenvalues.

Hence, the matrix $\boldsymbol{X}$ displays the following singular value decomposition:

$$\boldsymbol{X} = \boldsymbol{P}\boldsymbol{\Delta}\boldsymbol{Q}^{\boldsymbol{T}} \tag{20}$$

where $\boldsymbol{P}$ is the $I \times L$ matrix containing the set of eigenvectors for $\boldsymbol{X}\boldsymbol{X}^{\boldsymbol{T}}$ (or left singular vectors), $\boldsymbol{Q}$ is the $J \times L$ matrix that contains the set of eigenvectors for $\boldsymbol{X}^{\boldsymbol{T}}\boldsymbol{X}$ (or right singular vectors) and $\boldsymbol{\Delta}$ (which shares the same dimensions as $\boldsymbol{X}$) is a diagonal matrix of singular values from either $\boldsymbol{P}$ or $\boldsymbol{Q}$. Whether the singular values stem from either $\boldsymbol{P}$ or $\boldsymbol{Q}$ is irrelevant since both have the same positive eigenvalues.

In PCA, the components are obtained from the singular value decomposition of the matrix $\boldsymbol{X}$. Specifically, with $\boldsymbol{X} = \boldsymbol{P}\boldsymbol{\Delta}\boldsymbol{Q}^{\boldsymbol{T}}$ (see Equation (20)), the $I \times L$ matrix of factor scores, denoted as $\boldsymbol{F}$ is:

$$\boldsymbol{F} = \boldsymbol{P}\boldsymbol{\Delta} \tag{21}$$

The matrix $\boldsymbol{Q}$ provides the coefficients for the linear combinations used to yield the factors scores. This matrix can also be interpreted as a projection matrix since multiplying $\boldsymbol{X}$ by $\boldsymbol{Q}$ yields the values of the projections of the observations on the principal components. This can be shown by combining Equations (20) and (21) as:

$$\boldsymbol{F} = \boldsymbol{P}\boldsymbol{\Delta} = \boldsymbol{P}\boldsymbol{\Delta}\boldsymbol{Q}\boldsymbol{Q}^{\boldsymbol{T}} = \boldsymbol{X}\boldsymbol{Q} \tag{22}$$

TABLE I: List of Control Variables by group

Variable group	Variable name	Variable code	Variable Type	Variable Description
Individual characteristics	Gender	A_N01_T	Dummy	
	Age	AGEG5LFS	Integer	Age groups in 5-year intervals based on LFS groupings
	Educational level	B_Q01a	Integer	Highest level of qualification
Cognitive skills	Numeracy skill index	NUMWORK	Continuous	Index of use of numeracy skills at work
	Literacy skill index	PVLIT1	Continuous	Literacy scale score
Job characteristics	Economic sector	D_Q03	Integer	Economic sector at current work
	Firm size	D_Q06a	Integer	Amount of people working for employer
	On-the-job training	B_Q12c	Dummy	On-the-job training during previous year
Occupation	Occupation	ISCO1C	Integer	Occupational classification of respondent's job
Earnings	Earnings	EARNMTHBONUSPPP	Integer	Monthly earnings including bonuses for wage and salary earners

Notes : The Educational level is represented using the International Standard Classification of Education (ISCED) version of 1997. The classification of occupation is given at 1-digit-level of the International Standard Classification of Occupations (ISCO) from the 2008 version. The monthly earnings including bonuses are given in US dollars at Purchasing Power Parity.

TABLE II: Variables used to construct the indexes.

Variable group	Variable code	Variable Type	Variable Description
ICT Use	G_Q05c	Integer	Frequency of internet use for work related info
	G_Q05d	Integer	Frequency of internet use to conduct transactions
	G_Q05e	Integer	Frequency of computer use spreadsheets
	G_Q05g	Integer	Frequency of programming languages use
	G_Q06	Integer	Level of computer use
Manual	F_Q06b	Integer	Frequency of long physical work
	F_Q06c	Integer	Frequency of finger and hand use
Routine	D_Q11a	Integer	Level of task sequence change
	D_Q11b	Integer	Level of change in how to do the work
	D_Q11c	Integer	Level of change in the speed of work
	D_Q11d	Integer	Level of change in working hours
	D_Q13a	Integer	Frequency of learning from coworkers
	D_Q13b	Integer	Frequency of learning-by-doing
	D_Q13c	Integer	Frequency of keeping up to date with work related info
Abstract	G_Q01h	Integer	Frequency of reading schematics and maps
	G_Q02c	Integer	Frequency of writing reports
	F_Q05b	Integer	Frequency of solving complex problems
	F_Q04a	Integer	Frequency of need to influence people
	F_Q04b	Integer	Frequency of negotiating with people
	G_Q01g	Integer	Frequency of reading financial statements
	G_Q01d	Integer	Frequency of reading professional journals or publications

Notes : The majority of survey answers are presented in time frequency of tasks performed. The scale works in the following way : 1 = Never; 2 = Less than once a month; 3 = Less than once a week; 4 = At least once a week; 5 = Every day. The only exception is the Level of computer use (G_Q06) which can have three different answers: straightforward, moderate, and complex.

TABLE III: Task measures by country

	RTI	Manual	Abstract	Routine	ICT Use	Obs
United Kingdom	0.344	-0.228	-0.217	0.115	0.207	3237
Denmark	-0.204	-0.153	0.041	0.444	0.062	3119
Netherlands	-0.158	0.138	0.064	-0.054	0.157	2101
Norway	-0.273	0.223	-0.062	-0.282	-0.079	2346
France	-0.266	0.406	0.101	0.075	-0.117	2163
Poland	0.074	-0.106	0.024	0.037	-0.070	1911
Belgium	-0.291	0.215	0.024	-0.234	0.106	1724
Czech Republic	0.035	-0.034	0.114	-0.091	0.052	1627
Slovenia	0.283	-0.343	0.066	0.183	0.099	1354
Spain	-0.071	0.244	0.032	0.161	-0.162	1251
Cyprus	0.252	-0.057	0.051	0.404	–0.246	1217
Slovakia	0.153	-0.097	0.158	0.310	-0.058	1247
Lithuania	0.168	-0.161	0.422	0.533	0.155	1293
Italy	-0.087	0.239	0.250	0.348	0.201	865
Greece	0.352	-0.104	0.198	0.667	-0.275	597

Notes : the constructed sample for this table includes employed workers aged from aged from 20 to 64 years old currently working for which variables have non missing values. Workers in Armed Forces, Fishery and non specified occupations are excluded.

TABLE IV: Unconditional Differences of RTI across countries.

Country Dummies (Belgium as reference)	(1)	(2)
United Kingdom	0.6149*** (0.030)	0.6163*** (0.030)
Denmark	-0.1376** (0.030)	-0.0757*** (0.030)
Netherlands	0.0986*** (0.032)	0.0996 (0.032)
Norway	-0.0332 (0.031)	-0.0278*** (0.031)
France	-0.0606* (0.031)	-0.0545 (0.031)
Poland	0.3727*** (0.033)	0.3709*** (0.033)
Czech Republic	0.3779*** (0.034)	0.3770*** (0.034)
Slovenia	0.6123*** (0.036)	0.6150*** (0.036)
Spain	0.2246*** (0.037)	0.2174*** (0.037)
Cyprus	0.5817*** (0.037)	0.5730*** (0.037)
Slovakia	0.5353*** (0.036)	0.5321*** (0.036)
Lithuania	0.5780*** (0.035)	0.5777*** (0.035)
Italy	0.3043*** (0.040)	0.3043*** (0.040)
Greece	-0.7208*** (0.047)	0.7130*** (0.047)
ICT Use		-0.0190*** (0.003)
Intercept	-0.5259*** (0.024)	0.5175*** (0.023)
R-squared	0.077	0.102

Notes : Dependent variable is RTI index. We find in parentheses the standard errors. The significance levels are: *** for $\rho < 0.01$, ** for $\rho < 0.05$ and * for $\rho < 0.1$.

TABLE V: Conditional Differences of RTI across countries

	(1)	(2)	(3)	(4)	(5)
Individual characteristics					
Gender	−0.119***	−0.0941***	−0.1136***	−0.1057***	−0.1071***
	(0.011)	(0.011)	(0.012)	(0.012)	(0.011)
Age	−0.0053**	−0.0104***	−0.0167	−0.0111	−0.0116***
	(0.003)	(0.003)	(0.003)	(0.003)	(0.003)
Educational Level	−0.0125***	−0.0083***	−0.0145***	−0.0056	−0.0047**
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Cognitive skills					
Numeracy Score		0.0754***	0.0934***	0.1055	0.1285***
		(0.006)	(0.006)	(0.006)	(0.006)
Literacy Score		−0.0021***	−0.0021	−0.0019***	−0.0018***
		(0.000)	(0.000)	(0.000)	(0.000)
Job characteristics					
Economic Sector			0.1490***	0.1623***	0.1517***
			(0.011)	(0.011)	(0.011)
Firm size			−0.0122**	−0.0116**	−0.0108**
			(0.005)	(0.005)	(0.005)
On-job-training			−0.1547***	−0.1592***	−0.1618
			(0.012)	(0.012)	(0.012)
Occupation				0.0501***	0.0430**
				(0.004)	(0.004)
ICT Use					−0.0316***
					(0.004)
Intercept	−0.2047***	0.2189***	0.3870***	−0.0082	−0.0258
	(0.037)	(0.060)	(0.064)	(0.071)	(0.071)

Notes : Dependent variable is RTI index. We find in parentheses the standard errors. The significance levels are: *** for $\rho < 0.01$, ** for $\rho < 0.05$ and * for $\rho < 0.1$. Similar to Table IV, the reference for country dummies is Belgium.

TABLE VI: Oaxaca-Blinder Estimation Results

	(1)	(2)	(3)	(4)	(5)
Individual characteristics					
Gender	−0.3695***	−0.3315***	−0.2929***	−0.3022***	−0.3002***
	(0.008)	(0.008)	(0.008)	(0.008)	(0.008)
Age	−0.0836***	−0.0926***	−0.0917	−0.0847	0.0853***
	(0.002)	(0.002)	(0.002)	(0.002)	(0.002)
Educational Level	0.0496***	0.0389***	0.0364***	0.0253***	0.0244***
	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)
Cognitive skills					
Numeracy Score		0.0680***	0.0550***	0.0396***	0.0111**
		(0.004)	(0.004)	(0.004)	(0.005)
Literacy Score		−0.0025***	−0.0022	0.0020***	−0.0019***
		(0.000)	(0.000)	(0.000)	(0.000)
Job characteristics					
Economic Sector			−0.0894***	0.1073***	−0.0945***
			(0.008)	(0.008)	(0.008)
Firm size			0.1064***	−0.1051***	−0.1034***
			(0.003)	(0.003)	(0.003)
On-job-training			−0.1111***	−0.1072***	−0.1036***
			(0.008)	(0.008)	(0.08)
Occupation				−0.0636***	−0.0544***
				(0.003)	(0.003)
ICT Use					0.0393***
					(0.003)
Intercept	−7.7099***	6.8032***	6.9090***	7.40892***	7.4328
	(0.023)	(0.040)	(0.043)	(0.048)	(0.047)

Notes : Dependent variable is RTI index. We find in parentheses the standard errors. The significance levels are: *** for $\rho < 0.01$, ** for $\rho < 0.05$ and * for $\rho < 0.1$. Similar to Table IV, the reference for country dummies is Belgium.